DEVELOPMENT OF SPIKE TRAIN ALGORITHMS FOR PHYSIOTHERAPY ASSESSMENT USING DEEP LEARNING APPROACHES

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A thesis submitted in
fulfillment of the requirement for the award of the
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ABSTRACT

Physiotherapy nowadays has become a demanding medication for curing bones related injuries and pain to restore someone's to health in order to gain back the ability to cope with daily living tasks. As the technologies of sensors have risen, smart physiotherapy monitoring systems become trendy researches due to its potential to enhance the quality of physiotherapy assessment. However, varied sensor technologies of physiotherapy assessment have lacked versatility and robustness. This research proposed a spike train feature extraction for physiotherapy assessment to enhance the patient's progression. However, the concerns are how capable is spike trains in achieving high accuracy as other related works on recognising and assessing rehabilitation movements. In this context, spike trains are defined as sequences of recorded times when neurons fire spikes or also known as action potentials. This study implemented a spike train as a primary method of feature extraction that illustrated a significant pattern for each exercise performed.Three datasets, UI-PRMD dataset, K3Da dataset, and Self-Collected dataset have been adopted in the studies to be encoded into spike trains formal representation which resulting to an average of 415 spike patterns. Next, the patterns of raster plots were being trained as the input into a deep learning framework to evaluate the accuracy of the pattern's uniqueness. Furthermore, this study makes use of the occurrence of spikes' number, which is known as firing rate, to distinguish movements' correctness and being compared with the deep learning evaluation measures to prove the efficiency of deep learning prediction. The proposed framework achieved recognition rates of 99.44%, 98.21%, and 100.00% for UI-PRMD, K3Da, and self-collected datasets, respectively. These results proved that the proposed framework achieved targetable accuracy for all datasets trained with various CNN architectures. Next, the experimental results of physiotherapy assessment indicate that the correctness prediction by the proposed framework closely follows the ground-truth value for the movements. This study is among the first successful attempts of implementing spike train into a deep learning

framework for a real-time-based rehabilitation session case study with promising results. Hence, spike train is the foremost choice as features that are hugely rewarding towards deep learning as it can visually differentiate each of the physiotherapy movements with unique patterns.

ABSTRAK

Fisioterapi kini dilihat menjadi permintaan tinggi dalam merawat kecederaan individu yang berkaitan tulang agar mereka dapat kembali melakukan rutin harian seperti individu biasa. Sejajar dengan pesatnya pembangunan penderia, sistem pemantauan fisioterapi pintar semakin giat dibangunkan kerana potensinya yang berupaya membantu keberkesanan penilaian fisioterapi. Walau bagaimanapun, ketahanan dan kepelbagaian teknologi penderia di dalam penilaian fisioterapi dilihat agak ketinggalan. Kajian ini mengutarakan pembaharuan penyarian fitur *spike train* bagi memperbaiki mutu kemajuan pesakit di dalam penilaian fisioterapi. Namun, yang menjadi kebimbangan adalah bagaimana *spike train* mampu mencapai ketepatan tinggi seperti penyelidikan yang lepas dalam mengenali dan menilai pergerakan rehabilitasi. Dalam konteks ini, *spike train* didefinasikan sebagai urutan masa yang direkod apabila lonjakan neuron meningkat atau boleh dikenalpasti sebagai potensi tindakan. Kajian ini menjadikan *spike train* sebagai kaedah utama penyarian fitur bagi memberi ilustrasi corak yang penting pada setiap ujian yang telah dilakukan. Tiga set data, data UI-PRMD, data K3Da, dan data *Self-Collected* telah dimasukkan ke dalam kajian ini dan diterjemah ke dalam wakil umum *spike train* di mana ia menjurus kepada purata corak sebanyak 415. Seterusnya, kami menganimasikan hasil corak tersebut ke dalam kerangka pembelajaran mendalam untuk mengenalpasti ketepatan corak yang unik. Tambahan pula, penggunaan bilangan lonjakan berlaku yang dikenali sebagai kadar tembakan dalam kajian ini dapat mengenalpasti ketepatan pergerakan dan dibezakan bersama ukuran penilaian pembelajaran dalaman sekaligus membuktikan kecekapan ramalan pembelajaran mendalam. Kerangka yang dicadangkan masing-masing telah berjaya mencapai kadar nilai pengiktirafan sebanyak 99.44%, 98.21% dan 100.00% untuk UI-PRMD, K3Da dan data yang dikumpulkan secara persendirian. Keputusan ini telah membuktikan bahawa set data yang dianimasikan di dalam kajian ini adalah tepat dan mengikut spesifikasi pelbagai seni bina yang disarankan CNN. Selanjutnya, keputusan eksperimen dari penilaian fisioterapi menunjukkan bahawa nilai ketepatan

ramalan daripada kerangka yang dicadangkan bertepatan dengan nilai sebenar untuk pergerakan. Kajian ini adalah antara percubaan pertama yang berjaya dalam melaksanakan *spike train* ke kerangka pembelajaran mendalam untuk kajian kes sesi pemulihan berasaskan masa nyata dengan hasil yang menjanjikan. Justeru, *spike train* adalah pilihan yang jitu sebagai ciri yang terbaik kepada pembelajaran mendalam kerana ianya sangat bermanfaat untuk membezakan visual bagi setiap pergerakan fisioterapi yang masing-masing mempunyai corak yang unik.

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LIST OF SYMBOLS AND ABBREVIATIONS

AAD	–	Average Absolute Deviation
AI	–	Artificial Intelligence
ADLCAP	–	Activity Daily Living Clinical Assessment Protocol
ANARX	–	Additive Nonlinear Auto-Regressive Exogenous
ANFIS	–	Adaptive Neuro-Fuzzy Inference System
ANN	–	Artificial Neural Network
BNN	–	Backpropagation Neural Network
BoS	–	Base of Support
CNN	–	Convolutional Neural Network
CMU-MMAC	–	CMU Multi-Modal Activity
CoM	–	Centre of Mass
DL	–	Deep Learning
DMM	–	Depth Motion Maps
DNN	–	Deep Neural Network
DTW	–	Dynamic Time Warping
EMG	–	Electromyographic
ERF	–	Enhanced Random Decision Forest
FMA	–	Fugl-Meyer Assessment
GPU	–	Graphic Processing Unit

GRBM	–	Gaussian Restricted Boltzmann Machines
HCI	–	Human-Computer Interaction
HMM	–	Hidden Markov Model
HNN	–	Hierarchal Neural Network
HOG	–	Histogram of Gradient
HOF	–	Histogram of Optical Flow
HOJ3D	–	Histogram of 3d Joint Locations
HON4D	–	Histogram of Oriented 4D Normal
HPTE	–	Home-based Physiotherapy Exercises
HSMM	–	Hidden Semi-Markov Model
ISMMAL	–	Integrated Sports Medicine Movement Analysis Laboratory
K3Da	–	Kinect 3D active
k-NN	–	k-Nearest Neighbour
KiReS	–	Kinect Rehabilitation System
LBP	–	Local Binary Patterns
LR	–	Logistic Regression
LTDP	–	Local Ternary Direction Pattern
LTP	–	Long-Term Potentiation
MAD	–	Mean Absolute Deviation
MHAD	–	Multi-Modal Human action Dataset
ML	–	Machine Learning
MLP	–	Multilayer Perceptron
MPE	–	Mean Percentage Error

MSR	–	Microsoft Research
NARX	–	Nonlinear Auto-Regressive Exogenous
NN	–	Neural Network
PCA	–	Principle Component Analysis
PHOG	–	Pyramid of Histogram of Gradient
RBF	–	Radial Basis Function
RDF	–	Random Decision Forest
REMOC	–	Rehabilitation Movement Classification
RGB-D	–	Red Green Blue Depth
RNN	–	Recurrent Neural Network
ROI	–	Region of Interest
ROM	–	Range of Motion
RULA	–	Rapid Upper Limb Assessment Scoring
PNN	–	Probabilistic Neural Network
SDK	–	Software Development Kit
SIFT	–	Scale-Invariant Feature Transform
SNN	–	Spiking Neural Network
SPPB	–	Short Physical Performance Battery
SVM	–	Support Vector Machine
TBI	–	Traumatic Brain Injury
TUG	–	Timed Up and Go
UI-PRMD	–	University of Idaho-Physical Rehabilitation Movement Data
UTD	–	University of Dallas, Texas

VERA	–	Virtual Exercise Rehabilitation Assistant
WHO	–	World Health Organization
WMFT	–	Wolf Motor Function Test
ZVC	–	Zero-Velocity Crossing

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Physiotherapy, a part of modern healthcare, is concerned with the development, maintenance, and restoration of body movement and functionalities after illness or injury [1]. Various types of diseases and illnesses need to be cured by doing several exercises in order to manage pain and prevent diseases. Medical experts or therapists have been trained to evaluate and treat people who have movement disabilities and inabilities to perform daily tasks due to an injury or illness. Strokes, brain injuries, motor disabilities, sports injuries, post-accident injuries, and Parkinson's disease are examples of diseases that undergo physiotherapy.

Stroke, also known as cerebrovascular accident or brain attack, is one of the top five leading causes of death and one of the top 10 causes for hospitalisation in Malaysia [2]. According to the World Health Organization (WHO), stroke ranks as the second leading cause of death. Physiotherapy can help stroke patients gaining muscle control and strength back depending on the severity of the stroke. 50% of stroke survivors suffer from an impairment of motor function that requires prolonged rehabilitation [3].

Patients usually will be given exercises or training within their own pace and tolerance levels. The training that adequate for a patient may not be equally adequate for others. Several types of physical therapy exercises depend on patients' particular conditions and physical capabilities. Table 1.1 summarises the exercises together with the examples and conditions.

Table 1.1: Types of exercises correspond to the conditions

Physical Therapy Exercises	Explanation	Examples of Exercises	Conditions
Range of Motion	Range of Motion (ROM) exercises help in moving joints to prevent stiffness.	• Active ROM • Passive ROM • Active-assisted ROM	• Arthritis • Sport injuries • Post-Surgical Healing • Caution
Muscles Strengthening Exercises	It is increasing muscle strength to gain better balance, mobility, and ability for healthy lifestyle.	• Squat • One-Arm Row • Modified Push-Up • Shoulder Press • Knee Extension • Bridging • Sit to Stand	• Weight control • Pulmonary diseases • Stroke • Heart diseases
Balance Exercises	Balance exercises can help people with proper balancing or people who have muscles weakness preventing them from sudden falls.	• Standing one foot • Walking in a straight line • Yoga, Tai Chi	• Stroke • Cardiac event • Elderly • Low Blood Pressure
Endurance Exercises	Increase breathing and heart rate to improve the health of the lungs and heart as well as improve a person's overall fitness.	• Waking • Stairs Climbing	• Parkinson's • Cardiovascular diseases
Flexibility Exercises	Stretching can help improve the human body to become more flexible and limber.	• Hamstring Stretch • Chest Stretch • Calf Stretch • Back Stretch • Shoulder Stretch •	• Back pain • Disc Diseases • Parkinson's
Post-Surgery Exercises	Surgery patients experienced pain, muscle contractions, and stiffness. Physical therapy can relieve these issues by gradually adjusting the physical conditioning	• Head Lift • Buttock Lift • Walking	• Depends on body parts surgeries

1.2 Problem Statement

In Malaysia, there were almost 20,000 patients undergo physiotherapy per hospital or rehab centre each year, incorporate with a multitude of disciplines of serious illness, such as stroke, Parkinson's, post – surgeries. This statistic was resulting in a large ratio of medical experts to patients with 1:600, respectively. Consequently, Malaysia aims to increase the number of physiotherapists to 19,000 by 2020 as to narrow down the ratio to 1:200 [4]. However, the need specialists in this sector are still high. Generally, patients need to be monitored while performing the movements so that the movements being executed correctly, and medical experts can track the progression. Nevertheless, the lack of experts make physiotherapy session delayed and cause discomfort to the patients and the caregivers as well.

On top of that, patients usually need to attend therapists at the clinic, and it is such a burden for the caregiver and the patients. It is so inconvenient for the patients, especially for elderly and bedridden patients, to travel back and forth once in a week for physiotherapy. Aside from that, patients may need to wear assistive devices such as sensors throughout the session. This leads to unpleasant training for patients. On the other hand, there are limited physical therapy equipment and also therapists allocated in a clinic or infirmary. Therefore, patients may have to wait longer to perform the exercises as the therapists are unable to assess them or the equipment is fully utilised by other patients.

There have been some significant attempts at engaging these problems such as the exploitation of serious games[5]–[9], wearable sensor technologies[5], [10]–[14], assistive technologies[15]–[19]. Those attempts were not wrong, but there is much room to improve. There is other revolutionary equipment that would help a rehab centre, physiotherapist or patient itself such as depth sensor camera which is low-cost and affordable for all the practitioners.

However, how far does this help the patients in knowing the progression?. The exercises somehow need to be monitored and assess in order to keep track of patients' progress. Physiotherapy assessment would help patients, as well as the experts in monitoring patients' progression towards a positive outcome. Hence, this study highlights the importance of the coalition between physical therapy and engineering; thus, the relationship can grow and fortify, allowing the technological developments to overcome the problems. The importance of the joint work between physiotherapists and engineers will be demonstrated by the demands identified at the rehab centres. Technological advances for physiotherapy are developing increasingly, seeking a more efficient and targeted therapy to improve quality of life and social inclusion of people.

1.3 Research Aim

Hence, this is where technologies take place in assisting the experts conducting the session. Home rehabilitation seems to be the way out for the complications occur, which provides patients with a more flexible method to do the prescribed movements. This has caught the interest of many researchers concerning machine learning approaches to design a productive home rehabilitation exercise and classification method. Different machine learning algorithms have been utilised for recognizing different physiotherapy movements by recognising different parts of the body[20]. This study focuses on spike train feature extraction to achieve significant patterns and high data accuracy both on training and testing data. This thesis intends to improve physiotherapy assessment by providing quantitative data to the therapists, including movement correctness percentage to the patients themselves. These directions in future works are vast to enhance methods for the physiotherapy assessment system.

1.4 Research Objectives

Generally, the goal of the study is to develop a spike train feature extraction for application in rehabilitation movements' recognition and assessment limitations. Hence, the main objectives of this thesis are:

i. To develop feature extraction algorithms based on spike train for physiotherapy movement recognition and assessment.
ii. To determine the most optimum classifier based on the proposed framework for classifying the features with several CNN architectures.
iii. To evaluate and validate the effectiveness of the proposed framework for rehabilitation movements' correctness predicted by deep learning approaches along with verification using Rehabilitation Movement Classification (REMOC).

1.5 Research Scopes

The details of the software tools, datasets, and performances measures are described as follows:

i. This study covered the revolutionary technologies of physiotherapy sector over the period ranging from 2010 until 2020 across the world.
ii. The study was evaluated among three datasets, which two of datasets are publicly available datasets, University of Idaho-Physical Rehabilitation Movement Data (UI-PRMD) and Kinect 3D active Dataset (K3Da). The other dataset is self-collected data developed in-house by Computer Networking Laboratory from Universiti Tun Hussein Onn Malaysia.
iii. The data employed in this study only restricted to the extraction of raw data from a depth-sensor camera, Microsoft Kinect Xbox 360.
iv. The exercises analysed in this study were chosen generally, which are not restricted to any illness, injuries, etc.
v. There are seven performance measures adopted in this research, which are Mean Percentage Error (MPE) and Mean Absolute Deviation (MAD) utilised in movements correctness validation, the accuracy of recognition rate to measure the performance of the proposed CNN, and accuracy of correctness, precision, recall, and F1-Score to validate the physiotherapy assessment.
vi. The software tools and design measurement for this research are as follows.
    a. MATLAB is used to capture self-collected data, prepare for the data partition, spikes pattern generation, firing rates derivation, and CNN classification. All the graphs are plotted in MATLAB.
    b. CNN simulation and training were run on a 2.5GHz Intel i5-3210M quad-core processor, 8GB RAM with Microsoft Windows.

1.6 Research Contributions

i. This study proposed an advancement on the physiotherapy session system, which is a spike train as an extract feature for physiotherapy movement recognition and assessment. A significant spike pattern has been developed for each of an exercise by plotting spike trains into a raster plot. Hence, each of the exercises presents a unique pattern which can be differentiated visually and computationally.

ii. Movements' correctness approach has been derived by estimating spike trains' firing rate in order to enhance the effectiveness of the self-physiotherapy session.

iii. A proposed CNN framework has been developed and outperformed the other CNN architectures by achieving excellent accuracies for both recognition and prediction.

iv. Proposed CNN framework is proven to successfully predict the correctness of movements as being compared to the MPE and MAD of average firing rates for a test and ground truth value. This proposed framework able to compete and achieve a significant result.

v. This study is among the first successful attempts of implementing spike train into a deep learning framework for a real-time-based rehabilitation session case study with promising results.

vi. Rehabilitation Movements' Classification, REMOC application has been developed entirely in MATLAB software, where it is a real-time physiotherapy session consisting of the movements' correctness and movements' classification features based on the proposed framework presented in this thesis.

1.7 Thesis Outlines

This thesis is organised into six chapters. Each of the chapters in the thesis was as follows:

i. Chapter 1: Introduction
In this chapter, this study briefly describes the background of the research, objectives, problem statements, scope of work, and contribution.

ii. Chapter 2: Literature Review
This chapter presents the review of current physiotherapy technologies and related works on the human activity recognition method by using a depth sensor camera, Microsoft Kinect. This chapter also briefly explain on spike train mechanism and its previous related work.

iii. Chapter 3: Research Methodology
This chapter covers the methodology taken to emphasize the contributions of the research work, algorithms, and implementation model of the proposed framework. This chapter also describes on UI-PRMD dataset, K3Da dataset, and self-collected dataset that being used for the experimental works.

iv. Chapter 4: Results and Discussion
This chapter discusses the overall experimental results for the proposed framework implemented to the datasets. Discussion and justification of the work are stated in this chapter.

v. Chapter 5: Application of spike train features in Rehabilitation Movement Classification (REMOC
This chapter briefly introduced REMOC, Rehabilitation Movements Classification System. A system that was implementing the proposed framework to assist medical experts in managing patients for rehabilitation sessions.

vi. Chapter 6: Conclusion and Recommendation for Future Works
The final chapter summarises the thesis, re-stating the contributions and suggests ideas for future works, and concludes the overall research work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Chapter 2 reflects the problems of physiotherapy assessment and examines the benefit of developing spike train features with deep learning approaches for this application. This chapter is written based on previous researchers' works and spike train development in various fields, including physiotherapy assessment. This study also discussed machine learning methods and compared to deep learning techniques with an overall objective of recognizing and assessing physiotherapy movements.

2.2 Definition of physiotherapy

Physiotherapy or Physical Therapy is a branch of health care that involves non-invasive methods of treatment and therapy for illnesses, weaknesses, and disabilities. This is a method of treatment that encompasses rehabilitation, injury prevention, healing, and promotion of holistic fitness. It focuses mainly on the movement science to resolve underlying physical issues caused by injury or disability and to help people recover, improve, and sustain the physical strength and energy. Using a variety of validated therapies and evidence-based natural approaches such as exercises and a range of massages, therapist experts help diagnose the condition and recommend a recovery plan that is ideally suited to enhance the physical well-being of the patients and to restore it to normality.

People seek physiotherapist to find lasting relief from the pain that could have been bothering for a prolonged period and restricting mobility due to several factors.

The pain and discomfort might be from injury, frozen shoulder, wrong posture, or any other external factor; the experts not only helps to relieve the pain but also recognise warning signs and prevent the pain from happening. Thus, regular physiotherapy can provide relief to people of all ages suffering from a variety of ailments, injuries, or disorders. Other benefits of physiotherapy include:

i. Lasting relief from pain – There may be some aches and pains in the body for a variety of reasons, such as suffering from an ankle injury during sports activities or chronic low back pain due to long hours at work; it certainly demands urgent treatment if the pain affects daily tasks. Regular physiotherapy not only helps to minimize or even relieve discomfort but also minimize painkiller tolerance that is costly and dangerous in the long term.
ii. Prevention from surgery – Although, sometimes, surgery may be necessary, physiotherapy may help altogether remove the need to go under the knife. The combination of exercises and rehabilitation with a range of medication helps remove pain from the root, heals damaged muscles, and promotes painless movement over some time. Nevertheless, if the patients already underwent surgery, physiotherapy helps in recovering and recuperating faster.
iii. Improved mobility and balance – Patients who recover from an operation or injury usually take time to return to normal. Mobility can be a difficulty, and it is impossible to do daily tasks. Physiotherapy can be of great help in these situations. It helps not only the body to regain muscle strength but also agility to move around safely.
iv. Manage age-related issues – As people ageing, people experience disorders of the bones, joints, or muscles such as osteoporosis and arthritis. Regular physiotherapy may be helpful in coping with these everyday issues and pains. It can also be preferred if a person had a knee and hip replacement surgery and looking for pain-reducing and heal faster.
v. Avoid dependency on medicines – Although pain medication can provide immediate relief from pain, it can be fatal in the long run for kidneys and liver. Therefore, physiotherapy is considered a healthier and more effective to manage the pain for treating long-term pain issues.

Physiotherapy can be needed at any age, whether it is a toddler, a young adult, or a senior. If one suffered any form of sprain, muscle injury, or condition, physiotherapy could help improve one's overall physical well-being and heals faster. Some conditions that might be essential for people to seek for physiotherapy for long-term benefits as tabulated in Table 2.1. Experts basically assess one's condition, educate the person on the pain and its related issues as well as develop a rehabilitation program specifically suited for the condition. Hence, one's can lead a healthy, fit, and pain-free life.

Table 2.1: Experiences and conditions for a patient who seeks for physiotherapy

Experiences	Conditions
Posture problem	Back pain, lower back pain, neck pain, shoulder pain, muscle weakness, scapular instability, poor muscle tone, muscle imbalance, hypotonia
Joint pain	Arthritis, osteoporosis, poorly aligned joints, lupus, joint instability, bursitis, degenerative joints, age-related joint ailments
Joint injuries	Sprains & strains in ankle, knees, elbows, shoulder, wrist etc., torn cartilage, dislocated or unstable joints, degenerated meniscus, joint hypermobility
Recovery from surgery	Hip replacement, athletic injury surgery, tendon surgery, knee replacement, ligament surgery, spinal cord injury surgery, reconstructive surgery, lymph node replacement
Soft tissue injuries	Tennis elbow, golfers elbow, whiplash, Achilles tendinitis, back & neck strain, rotator cuff injuries, tendinitis
Bruising & Swelling	Bruising following sports or any other related injury or surgery, contusions, swollen joints, chronic joint or muscle inflammation, lymphedema, lymphatic congestion

Based on the patients' condition, the experts may prescribe a treatment plan taking into account one or a combination of a type of therapies, as in Table 2.2. Using a variety of hands-on therapies, including physical therapy, to stretch sore joints and muscles, therapeutic massages to relax tense muscles, machines, and devices to treat pain-related issues.

Table 2.2: Types of physiotherapy and its explanation

Physiotherapy	Explanation
Massage & Manipulation	By using the movement of hands, massage can manipulate the body's soft tissues. It is considered to be the most effective for treating pain, aches, & movement disorder in the neck, shoulder, and back area, curing headaches and stress-related issues.
Movement & Exercises	An efficient exercise plan is a significant aspect of physiotherapy that people are frequently encouraged to underdo when healing from an injury or attempting to strengthen their equilibrium or movement rate. These exercises strengthen the muscles and joints, improve control, and avoiding recurring injury. For example, for someone who had a stroke or facing paralysis, some specific exercises will be prescribed for the targeted area.
Energy-based Therapy	Often known as electrotherapy, various energies such as currents or pulses are used to activate the nervous system. The electrical pulses contract the muscles to ease out pain and stress from the body where leads to effective healing. It is a pain-free treatment but maybe tingled while undergoing them. The energy-based therapy are Ultrasound, Laser Therapy, Shortwave Diathermy, etc.
Hydrotherapy	It is a water-based therapy where it is carried out in the water. The temperature of the water is generally between hot and mild to help the muscles relax and alleviate pain. Hydrotherapy works as the weight of the water push against the body during the exercises. This helps to promote proper blood flow in the body and reduce pain.
Paediatric Physiotherapy	Its aim to at helping children with developmental issues and physical problems as patients may face movement difficulties due to a range of conditions such as Cerebral Palsy, Development Delay, Down's Syndrome,.
Neurological Physical Therapy	Patients with Alzheimer's, Parkinson's, or some other form of brain injury may have major positive effects on physical exercises. This can reduce the impact of neurological disorders from spreading all over the system and improve body movement and coordination
Cardiovascular Physical Therapy	If one is having heart issues or regulation of blood and oxygen, a cardiopulmonary physical therapy will help reduce complications such as heart attack and pulmonary fibrosis; increase strength in core muscles and boost long-term endurance

This study focused on movement and exercise physiotherapy, as it is the standard rehabilitation in most of the world. Movement and exercises can be done anywhere with space, whether in the rehab centre, home, or public park. By doing exercises, one could get rid of the pain, muscles, and joints stiffness that limit the movements to do daily tasks. In contrast, exercise may take a prolonged time for a patient to be back on track and recover full health. One need to do the exercises prescribed by the experts repeatedly until one are progressing in terms of speed and intensity.

2.3 Physiotherapy Assessment

The effectiveness of an exercise can be shown by measuring the progression of a patient that are regularly followed the prescribed exercise with the number of repetitions daily. The progression also may motivate patients by showing the improvement since rehab program started. There are different components of exercises that can be measured, as an example, the frequency of someone being active, the intensity of the activity, the type of activity engaged, and the duration of that activity. However, frequently, it is more practical to get an overall measurement of one's activity over a period.

Assessing the movements or exercises may increase to achieve the goal of improved health. However, there are several approaches to evaluating physiotherapy assessment in a rehabilitation centre. At a community level, good evaluations can lead to program improvements, documenting positive results can attract to continue and expand programs, and communicating results can persuade other communities to adopt practical approaches [21].

2.3.1 Conventional Physiotherapy Assessment

There are tons of rehabilitation centre has been built in this century. The rehabilitation centre helps patients with illnesses in order to cure the illness or to assist in daily activities. Each of the rehabilitation centres might have different approaches to physiotherapy assessment. Below is an example of approaches to measuring physiotherapy exercises that are used nowadays.

i. Existing Records

   This includes using information that is routinely collected, for example, census information, surveys from patients, or government data. However, sometimes the existing data does not meet the needs because of the broadness of the records, not focus on the specific targeted area, and outdated formatting that may have been gathered improperly.

ii. Indirect Measures

   Indirect measures basically rely on self-report. Patients need to estimate how much activity being done in a period. This approach can be useful because of the minimal cost needed and easy to complete. However, the issues on relying on the recall may be appropriate for some older populations and people with dementia. Plus, there are other issues, such as dishonest, on telling the truth as to get a favourable result of the assessment.

iii. Direct Measures

Direct measures use technology to measure activity levels, and this is usually as a device that measures and record movement. This might be a simple pedometer, an app on a smartphone, a sophisticated movement tracker, or a wearable sensor. This is the most used approach in many rehab centre as it is considered to be more accurate than self-report measures. However, the approach is costly and may not be appealing to some patients, e.g., the elders. Plus, the approach also has limitations, including:

a. Inability to detect very minimal walking speeds.
b. Inability to measure movement in abnormal gait patterns.
c. Inability to gather data on certain types of activity, e.g., if a wearable sensor is placed on the lower limb, it is doubtful that the upper limb movement is observed. This concerns wheelchair users or someone who practices chair-based exercise.

Evaluation of physiotherapy assessment is challenging and often hindered by the challenge of employing an accurate and reliable measure that also adequately addresses the research problems [22]. Both indirect and direct measures contributed well to physiotherapy assessment; however, because of the barriers to accessing technology, indirect measures are still frequently adopted [23]. Despite the argument, direct measures appear to provide slightly more consistent results.

On the other hand, all three approaches explained are still valid and utilised in rehab centres. Figure 2.1 depicted the flow of a rehabilitation session in most of the centre. Each of the patients was prescribed the exercises based on the capabilities and conditions. In a session, patients were attached to the specific rehabilitation devices based on the illnesses. Throughout the session, the patient's performance data were interpreted to be evaluated by the medical experts and also will be stored for research. Once the performance has been evaluated, therapists will explain the feedback to the patients.

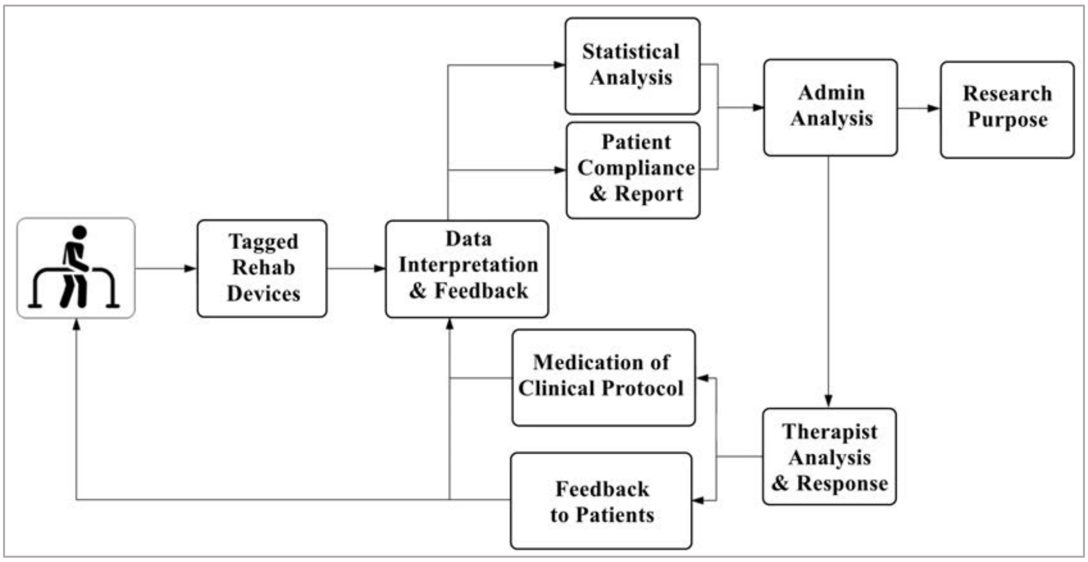


Figure 2.1: General flow of rehabilitation session in a rehabilitation centre

On the contrast, rehabilitation session in the centre is incompetent for bedridden patients or disabled patient as the needs to travel back and forth. Plus, the waiting game for a physiotherapists availability as well as the rehabilitation devices. The awful truth for most of the patients as the patients need to wait for the turns with an uncomfortable state. Therefore, this focused on a new direct measure for physiotherapy assessment, by utilising a 3D sensory camera, Kinect, which overcomes all the limitations mentioned.

2.4 Kinect-Based Physiotherapy Assessment

Virtual reality-based rehabilitation offers a highly interactive system with many documented benefits specifically to strokes patients [24], and a large variety have recently come to the forefront. Kinect is a 3D somatosensory camera that can input spontaneous data like human gestures, images, and voice etc. [25]. Patients or users can freely do the training without having to wear any sensors and also interact with the computer by making motions in front of Kinect. Kinect is beneficial to extinguish the space limits, and patients can manipulate with bare hands.

Furthermore, Kinect is a low-cost technology that makes its popularisation possible. With Kinect, people nowadays can execute training or rehabilitation exercises at home instead of frequently travel to the Rehabilitation Centre. The Kinect has been examined in healthcare to monitor and improve the process of physical therapy and rehabilitation[26], [27]. Patients can now do home exercises and being monitored by Kinect. Correct adherence to supplemental home exercise is essential for safe, effective, and efficient rehabilitation care [28]. Table 2.3 summarizes the limitations of the approaches, as explained in the previous sub-section, and how the specification of Kinect overcome the limitations.

Table 2.3: Limitations of conventional approaches on physiotherapy assessment

Limitations	**Solutions by Kinect's Features**
Existing records are too broad and not targeted in a specific area	The programmatic gestures detection mainly tracking the position and movement of specific joints[29]–[31].
Dishonest, relying on recall of patients	Data from Kinect can be extracted out or be uploaded in Cloud[32]–[34].
Wearable sensors do not detect full-body movements when placed on a lower limb.	Kinect consists of 20 – 25 joints, where not even a single joint will be opted out despite any position of the patient was[11].
Inability to measure abnormal gestures	
Travel back and forth to rehab centre discomfort patients	Kinect is portable and can be implemented in-house so that patients can do home-based exercise monitored by Kinect[10], [11], [30], [35].
Waiting games in the rehab centres	Kinect basically can detect up to six people at a time [36], [37].

Until now, Microsoft Kinect, an active system for the assessment of human activity, has released two versions of Kinect Sensor, which Kinect v1 and Kinect v2. The Microsoft Kinect for Windows sensor v1 was launched in November 2010 while Kinect v2 was released just recently. Unlike contact sensors, Kinect is a non-contact sensor and is not wearable. It also does not require a battery replacement or charging port. Table 2.4 illustrates the technical specification for Kinect v1 and Kinect v2.

Table 2.4: Technical specification comparison of Kinect v1 and Kinect v2

Feature	**Kinect v1**	**Kinect v2**
Color Camera	640 x 480 @ 30 fps	1920 x 1080 @ 30 fps
Depth Camera	320 x 240	512 x 424
Max Depth Distance	~4.5 M	~4.5 M
Min Depth Distance	40 cm in near mode	50 cm
Horizontal Field of View	57 degrees	70 degrees
Vertical Field of View	43 degrees	60 degrees
Tilt Motor	Yes	No
Skeleton Joints Defined	20 joints	25 joints
Full Skeleton Tracked	2	6
USB Standard	2.0	3.0
Supported OS	Win 7, Win 8	Win 8

Recent studies have shown that Kinect Sensor can be used to quantify clinically relevant parameters of gait [38], [39], and posture [40]. Kinect-based virtual stepping therapy is effective for post-stroke rehabilitation of gait [41]. Boundless of applications and research on Kinect-based were conducted even now. The most leading applications on Kinect-based for rehabilitations exercises are Exercise Games and Serious Games.

Exercise games, known as exergames, intend to integrate natural human motion and entertainment in order to promote elderly exercise. In contrast, serious games aim to concurrently rehabilitate motor-impaired users and monitored patients' progress [42].

However, exercise games and serious games have to come to the limits as the requirements for clinical data capture for specific limb movements cannot be achieved. Below is the summarization of the limitations for exergames and serious games [42]:

i. Designated games specifically for diagnostic usage are limited to non-occluding movements. This implies that standard stroke impairment level tests requiring extensive occluding movement sets may be untenable for a Kinect-based system to capture.

ii. Diagnostic potential for extremities is limited to gross movements, as subtle movements of the hand and foot are currently outside the Kinect's capture sensitivity.

iii. Games targeted at rehabilitation may be prone to "cheating," which means unnatural.

iv. An appropriate response to failure and poor performance, if not accounted for during game design, can inherently limit positive outcomes due to demotivation.

v. The benefits of the games mainly studied for short term and small-sized studies.

Besides, the games itself having cons as it is not suitable for all ages. For example, exergames and serious games are built only for young and middle ages people. It is inadequate for the elderly as the elderly might have secondary disabilities such as eyesight, hearing, speech problems; thus, it is inconvenient for the elder to focus on the screen as well as the games. The games were also irrelevant for bedridden patients. Hence, this study focuses on Kinect-based physiotherapy assessment as this system that combines optical- and radar-based technologies for human detection, tracking, and activity recognition.

Vision-based human action recognition is an orderly way to recognise and perceive the movement of people in camera-captured content. It composes of fields such as Biomechanics, Machine Vision, Image Processing, Artificial Intelligence, and Pattern Recognition [43]. Human activities can be classified into four categories, which are actions, gestures, interactions, and group activities [44]. Motion recognition composes of many actions such as walking, sitting, standing, running, waving. Figure 2.2 defines the steps in the human motion recognition system.

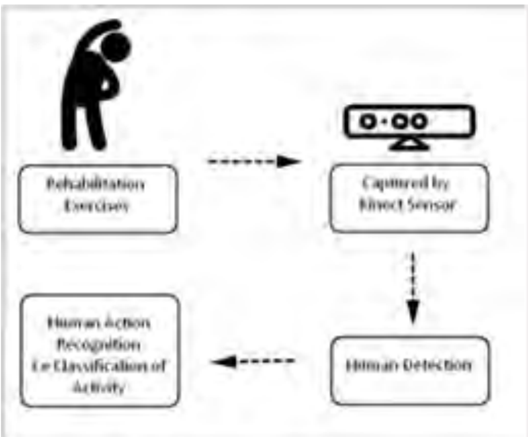


Figure 2.2: General framework of human action recognition

2.5 Human Detection

Human detection is an early stage for human action recognition. Detecting humans can be divided by many categories depends on human body parts such as an upper limb, lower limb, hands, arms, head, legs. Each of the body parts needs different detection methods to match the accuracy of the evaluation.

Computer vision and machine learning algorithms have been adopted to confront the problem of human detection in videos. There are many solutions and techniques introduced based on various scenarios, including variations in illumination and poses, as well as background clutter. Dalal & Triggs report impressive results on human detection [45] by implementing a Histogram of Gradient (HoG) as low-level features and outperformed other features such as wavelets[46], PCA-SHIFT [47], and shape contexts[48]. Zhu et al. propose a rejection cascade using HoG features to improve the detection speed [49] while Zhang et al. come up with a multi-resolution framework in order to cut down computational cost[50].

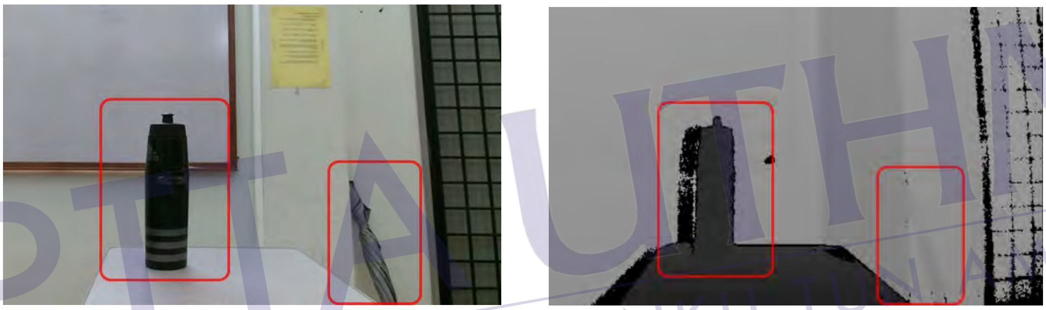
In contrast, Lowe proposed the Scale-Invariant Feature Transform (SIFT), which has high accuracy and low computation time [51], which also being employed by Khaledian et al. for hand gesture recognition [52]. Ke and Sukthankar attempt to further improve the method by introducing PCA-SIFT [47]. Next, Speeded Up Robust Features by Bay et al. being introduced as it is shown to yield comparable or better results to SIFT[53].

Perhaps, the most recent, promising approach is detection by RGB-D cameras, such as the Kinect sensor. RGBD sensors are much more privacy-preserving than traditional video cameras because of human silhouette made it possible to achieve a higher level of privacy by only using a skeleton to represent a person[54]. This detection can be split into two standard methods, which are Depth Mapping and Skeletal Joints. The next sub-section discussed on related work for both depth maps and skeleton joints in physiotherapy-based. However, this study focused on exploiting skeleton joints data extracted from Kinect RGB-D sensors as the input for spike train analysis since skeletal data seems to promise and slightly better accurate than depth data in detecting physiotherapy movements [55], [56].

2.5.1 Depth Maps

Depth imaging technology has advanced adequately over the last few years, finally reaching a consumer price point with the launch of Kinect. Depth images provide depth information of an object or also known as z-information of an object in the real world. Depth maps can be collected through Stereo Camera, Laser Triangulation, etc. It is also widely used in many 3D vision algorithms recently.

The intensity values in an image represent the distance of the object from a viewpoint. As illustrated in Figure 2.3 a) there is a bottle and an umbrella in an area. The depth image in Figure 2.3 b) shows luminance in proportion to the distance of an object from the camera. The nearer object to the camera, which is the bottle, is darker while the further object, the umbrella, is lighter.



(a) Normal image (b) Depth image

Figure 2.3: Comparison between normal and depth image using Kinect v2

In the last few years, solutions for activity recognition have been presented; the work intended to extract features from depth data such as [57], where the work is presenting the adaptive spatial-temporal pyramid to improving in retaining the spatial and temporal orders. Truong et al. developed a simple method from hand gesture recognition that achieve accurately in real-time using depth information from Kinect Sensor [58]. Author applying thresholds to the hand point that is tracked by the Bayesian Object Localisation method in the depth image to determine the hand region. Next, Samad et al. applied background segmentation with an improved adaptive Gaussian mixture algorithm to the depth map to detect moving objects [59].

Whereas the raw depth map has been smoothened by applying two filtering methods, which are pixel filtering and context filtering [60]. Then, the depth map is encoded through the proposed Local Ternary Direction Pattern (LTDP) feature descriptor and utilised by the SVM classifier. The result turns out that LTDP outperformed the other five existing descriptors (LBP, LTP, HOG, PHOG, CENTRIST), and the nonlinear effect of the SVM classification task was reduced by using LTDP on the depth map.

Yang et al. proposed HOG in Depth Motion Maps (DMM-HOG), which applies the HOG descriptor on depth motion maps. It is computed by taking the difference of the depth maps in two consecutive frames, thresholding the difference, and aggregating the difference. Then, the work extract DMMs from the front, top, and side views [61]. Next, Xia et al. present a human detection method by depth information by Kinect, and the results can adequately detect the persons in all poses and appearances also provide an exact estimation of the whole-body contour of a person [62].

On the other hand, Ni et al. propose a method for action recognition by combining depth maps with RGB videos. The method is done by identifying the interest points in RGB videos, extracting HOG/HOF features, and LDP features from RGB videos and depth sequences, respectively, and concatenating the RGB and depth map features [63]. It shows that the information in RGB videos and depth map sequences are complementary to each other. There are extensive studies on depth images approaching rehabilitation, and physiotherapy assessment have been illustrated in Table 2.5.

Bakar et al. [64] and Sosa et al. [65] employs Region of Interest (ROI) in the segmentation phase to minimise the area and remove unwanted objects that appear around. Sinha et al. [66] proposed an algorithm in Depth-based segmentation and PCA to improve the accuracy of Kinect for upper body rehabilitation applications.

Next, Yao et al. [67] proposed a Kinect-based rehabilitation system for both therapists and patients. The work evaluates the time sequence-based data by implementing Cross-Correlation as the method is well known for detecting common periodicities. The work also employed DTW to compare whether the patients have done the exercises at the same rate as the skeleton frame sequences. It is to compare and find optimal alignment between two given time-sequences. Furthermore, Ye et al. [68] utilise DTW to compute a distance matrix for gait pattern extraction while Su et al. [35] applying DTW measure the similarity of joint data between "at home exercises" and “in hospital exercises.”

Table 2.5: Kinect depth maps features for physiotherapy assessment

First author / Year	Health Disorder & Exercises	Dataset	Proposed Method	Limitations/ Strength
Y. J. Chang, 2013. [74]	Cerebral Palsy - Upper limb	Depth information	Kolmogorov-Smirnov Test	Only based on two CP cases.
B.Penelle, 2013. [75]	Lower limb	Depth images	GPU based Particle Filter	Robust to a certain degree of noise
S. Nomm, 2013. [69]	Motor Functions Therapeutic - Dynamic ROM	Depth information	NN-based ANARX	Complex as large number of parameters need to be identified
T. Watanabe, 2014. [76]	Elderly - toe lift, heel lift, Knee extensions	Depth Images -Seven subjects (75 – 85 yo)	Average Recognition Rate	Poor in joint positions' estimation
L. Yao, 2014. [67]	Rehabilitation Exercises	Depth Images	DTW	Only based on therapists' experience
C. J. Su, 2014. [35]	Post-injuries -Shoulder rehab exercises	Depth information	DTW Neural Network Fuzzy Logic	Model exercise are not generalised for all patients
M.Z. A. Bakar, 2015. [64]	Wrist Hand Injury -Hand Deviation	3D data Depth Data RGB Data	ROI Hand Contour K-Curvature	Limited data for validation
L. Omelina, 2016 [77]	Patients' recognition	Depth Images	LBP Chi-Square K-Mean	Discriminate between active and passive motion
G. D. Sosa, 2015. [65]	Multiple Sclerosis -shoulder elevation, abduction, hip abduction	RGB Data 2D with 30fps -Four subjects (24 – 39 yo)	ROI Background subtraction human silhouette skeletonisation	Only restricted for certain joints and front view measurement
S. Sinha, 2016. [66]	Upper Limb ROM exercise	RGB Depth -Ten subjects (21- 55yo)	PCA Proposed algorithm	Provide reliability for clinical assessment posture
M. Ye, 2017. [68]	Stroke -walking exercises	Depth map	DTW NARX Kernel Filter Enhanced RDF	Cost-effective, portable gait assessment system
D. Nahavandi, 2017. [70]	Musculoskeletal Disorder -Shoulder, Elbow, Trunk, Neck	Depth images -RULA Scoring	DCF Feature Extraction RDF	Only analyse static postures
J. Collins, 2017. [8]	Stroke - arm extensions, chest sway, waking	Depth data	HON4D	Ability to perform assessment on critical metrics
V. Nghia, 2017. [71]	Arm Flexion, Elevation, Abduction	Skeleton joint Depth images	Hand's Palm Status Detection	Low authentication

Su et al. then evaluate the performance by using the Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrates a neural network and a fuzzy logic [35]. Nomm et al. practised Neural Network-based model, NN-based ANARX (Additive

Nonlinear Auto-Regressive exogenous), in the monitoring system as it can adjust the system according to the specific needs of each patient [69] whereas Ye et al. used NN-based on nonlinear autoregressive with exogenous (NARX) for gait phase classification and Enhanced Random Decision Forest (ERF) for missing features cases [68]. Next, Nahavandi et al. trained a Random Decision Forest (RDF) for generalising a learning model in order to discriminate between seven RULA-scored sets of postures [70].

In contrast, Collins et al. achieved to recognise several human actions by stroke patients with high certainty by employing HON4D as a global descriptor [8]. Nghia et al. proposed an algorithm to compute discriminative features, depth of wrist, by building a mapping table between the differences of joint bone depth and head depth as Kinect provided [71]. Consequently, depth maps are the right approach for detecting human action as it insensitive to changes in lighting conditions; hence it even works in low ambient light conditions [72]. Depth maps properties also convenience to works with specific feature descriptors, which spikes the evaluation performance [71], [73].

2.5.2 Skeleton Joints

Skeleton joints involve in combination number of joints that define body parts such as the head, shoulders, neck, and arms. This process describes a massive number of dimensions, and it describes unique individuals such as shapes, sizes, postures, motions. Each version of Kinect has a different number of joint types that made up a skeleton. For version 1 (Figure 2.4 (a)) comprises 20-joint types, while version 2 (Figure 2.4 (b)) comprises 25-joint types with additional five joints from Kinect v1. The new joints in Kinect v2 are Spineshoulder, HandTipLeft, ThumbLeft, HandTipRight, and ThumbRight. The details of each joint number have been explained in Table 2.6.

Skeleton Joints features are incompatible with working alone, as it is inadequate to identify various human actions. Hence, there are many developed methods of visual representations and machine learning methods in order to fully achieved skeleton features in human action recognition.

Raptis et al. successfully used skeleton positions in a real-time dance classification by employing Principal Component Analysis (PCA) on torso joints positions. This is done to determine a human torso surface as well as defining a human pose with the spherical angles within the limb joint positions and torso surface [78]. Fourier transform is also being utilised over time to describe the temporal structure of actions.

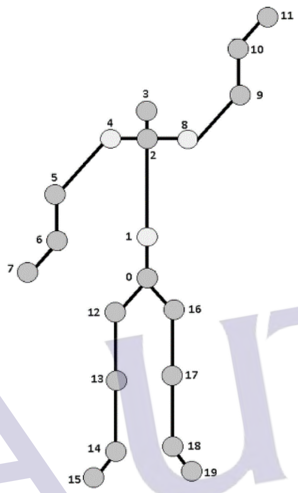
Yang et al. proposed a new type of feature based on position differences between joints, Eigenjoint, to represent actions that combine action information [79]. The positions difference is extracted from all the pairs in one frame, the joint of continuing frames, and the joints of the initial frame with another frame to grab the structure of human postures. The work also applied PCA to the features to extract the crucial data for action recognition, "eigenjoints", then undergo action classification by applying nearest-neighbour classifier.

Xia et al. introduced an approach for human action recognition with a Histogram of 3D joint locations (HOJ3D). It extracts the histogram of spherical coordinates of the joint positions in a coordinates system that uses the hip joint as an origin [80]. The work also employed Shotton et al.'s method to extract 3D joint location from a depth image by employing a local mode-finding approach based on mean shift with a weighted Gaussian Kernel to compute the confidence-scored 3D position estimation of body joints [81].

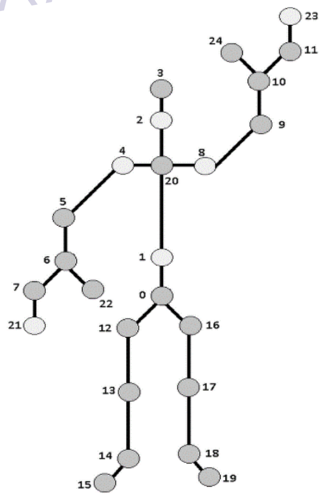
Chaundry et al. illustrated the bio-inspired dynamic 3D discriminative skeleton feature by using linear dynamic systems to model the dynamic medial axis structures of human parts. The paper considered a discriminative metric to compare sets of linear dynamics systems for action recognition. Table 2.7 summarises relevant papers on Kinect based on physiotherapy and assessment using skeleton joints. Each paper proposed different methods for different rehabilitation exercises.

Janani et al. apply skeleton normalisation for pre-processing data to overcome discrepancies when a real-time quantitative assessment of exercises performed by TBI patients at home matched with the template exercises performed in the clinic [82] as well as in Jiang et al. [25], Lin et al. [83], Lee et al. [6], employ normalisation to compare and evaluate different skeleton models. In contrast, Cappecci et al. utilises Zero-Velocity Crossing (ZVC) to locate starting and ending points for human motion segmentation in order to identify moving points [84]. Han et al. scaling the values of joint points by implementing Z-Score Normalisation to improve the performance of a deep learning algorithm [85].

Further, on exercise assessment, Cappecci et al. [84] compared a Histogram Semi-Markov Model (HSMM) based algorithm to monitor and evaluate rehabilitation exercises with Dynamic Time Warping algorithm resulting HSMM outperformed DTW as HSMM demonstrated scores correlated better with the clinical scores. However, Janani et al. [82] stated that DTW surpasses the Direct Comparison and Cross-Correlation method as DTW able to give a significant score and achieve higher separation between most of the similar and dissimilar videos. DTW is also being used by Jiang et al. [25] and Anton et al. [86].



(a)



(b)

Figure 2.4: (a) 20-Joints of human body in action recognition through Kinect v1; (b) 25-Joints of human body in action recognition through Kinect v2

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